A Multi-level Approach to Link Smooth Driving with Safe Driver Behavior

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ABSTRACT

Smooth driving is the most critical dimension of the general notion of eco-driving and may have a potential impact on accident risk. Nonetheless, research thus far has not shed light on the relationship between smooth driving and safety-related driving behavior. This paper aims to understand the strength of the relationship between smooth and safe driving. To this end, a methodological approach that combines a trip and driver level analysis is proposed based on the K-Means algorithm for trip clustering and driver evaluation and the Data Envelopment Analysis for safety efficiency evaluation of drivers. Data used are recorded during a naturalistic driving experiment with more than 760 participating drivers. Results indicate that there exist 3 clusters of different levels of smooth driving on a trip level. Drivers' efficiency evaluation demonstrated that there are significant differences in attributes of most and least efficient drivers. A strong relationship is then revealed between overall safe efficiency on a driver level and smooth driving on a trip level by estimating Kendall's tau and Spearman's rank correlation of the two rankings (safe and smooth driving). These findings show a potentiality for predicting the occurrence of safe driving through smoothness characteristics observed on a trip level and vice versa and could be exploited to provide personalized feedback to drivers to improve their driving behavior in terms of smoothness and safety.

Keywords: Smooth Driving, Safe Behavior, Driving profiles, Clustering Algorithm, Data Envelopment Analysis, Ranking Correlation

BACKGROUND AND MOTIVATION

Driver behavior analytics is an emerging concept with several important applications during the past decades. As we are entering the Big Data era, new data collection schemes and advanced modeling techniques related to Machine Learning and Artificial Intelligence are available. These create considerable opportunities for large-scale collection of new data such as driver physiological indicators, trip driving time and conditions, congestion, road surface and environment conditions, and detailed weather and spatial information, for the analysis of driving behavior (*1*, *2*).

Even in the ever-changing transportation system where innovations of Information and Communication Technologies (ICT) together with the introduction of new mobility services drastically affect urban mobility, drivers remain the protagonists. Therefore, the understanding of driving behavior's dynamics still remains a very active field of research. Recent advances in cloud computing, Artificial Intelligence (AI) and the Internet of Things (IoT) together with the high penetration rate of smartphones provide unprecedented capabilities to collect, store and analyze large volumes of data coming from heterogeneous sources that enable the monitoring and understanding of driving behavior for each individual (*3*). A great number of studies have confirmed the efficiency of exploiting crowd-sensed driving data in driving behavior research (*4*, *5*).

Different drivers execute a variety of behaviors regarding the way they alter their longitudinal (accelerate, decelerate) and lateral position (steering), the distance they keep from the preceding vehicle and also, and how far they drive from the speed limit (speeding). Specifically, the risky driving style is characterized by behaviors such as driving with speed excess and performing speed limit violations (*6*). Another critical aspect of driving behavior refers to the level of aggressiveness during driving, where the driver usually performs immoderate accelerations and decelerations (harsh acceleration (HA) and harsh braking (HB)) and improper lane changes (*7*, *8*). It should be noted that although both aggressiveness and risky driving are associated with a high risk for accidents and traffic safety hazards, and therefore constitute an unsafe way of driving, some studies highlighted that it is possible to drive in a risky manner without being aggressive at the same time (*6*, *9*).

The modern shift towards the sustainability of transport and the reduction of the environmental footprint has brought to the forefront of research the concept of "eco-driving" since it is linked with reduced fuel consumption and greenhouse gases (GHG) emissions (*10*). Eco-driving has received many definitions in the literature as it refers to a multidimensional decision-making process involving both smoothness while driving, but also other strategic choices of the driver such as route selection and vehicle maintenance (*11*). In this paper, the analysis is narrowed to the aspect of driving smoothness disregarding the strategic and tactical decisions of the driver (*12*).

The adoption of a smoother driving style involves a gradual approach to both accelerating and braking, as well as maintaining a constant speed (*11*). It is estimated that eco-driving is capable of reducing fuel consumption by 15% to 25% and GHG emissions by about 30% (*13*, *14*). In order to enjoy the long-term benefits of adopting an eco-friendly driving behavior, researchers have highlighted the importance of providing feedback on the actions of drivers (*15*).

Many studies in driving behavior literature (*3*, *16*, *17*) have focused on measuring driving safety efficiency, the microscopic driving factors influencing it and the methodologies for driving behavior data collection and analysis (*3*, *18*). In this research field, efficiency is defined as the number of driving metrics recorded for a specific period or distance that a driver is being monitored (*3*, *19*, *20*). Drivers are considered driving units that make decisions about the number of events occurring, the time of mobile phone usage and speed limit violation within a given mileage range. Driving safety efficiency in this study refers to the amount of driving events (harsh braking, harsh acceleration, mobile phone usage, speeding) that occurred within a certain driving distance, as also used in (*3*, *21*). The most efficient drivers are those with the least number of events.

Previous research on efficiency analysis has shown that Data Envelopment Analysis is an effective methodology to measure driving efficiency (*3*, *21*, *22*). Although DEA is mostly used in business, economics, management and health, it has also been implemented in transport fields in assessing public transportation system performance (*23*), as well as traffic safety studies (*24*, *25*) where it was shown to be equally useful as in the fields stated above.

It is observed that eco/ smooth driving and safety behavior are two notions that are separately studied thus far, although they share common characteristics (*26*). By observing the relations between them, one would be able to identify the presence of a certain behavior, such as less risky driving, based on characteristics of the other, e.g., smooth driving, as a proxy. This paper aims to investigate the aforementioned interrelation between different levels of smooth driving with the overall driving performance, in terms of safety, for each individual driver. For this purpose, a large naturalistic driving dataset is used, first to detect the smoothness of driving at a trip level using an unsupervised learning technique and, then, Data Envelopment Analysis (DEA) is applied to identify driving safety frontiers at a driver level. The outputs of the two methods are combined to provide some critical insights on whether smooth driving on a trip level is strongly related to safe driving on an overall driver level.

The three research questions that this study addresses are:

1) What are the dissimilarities, in terms of unsafe driving habits, among drivers that belong to different safety efficiency levels?
2) What are the different trip/driving profiles with respect to smooth driving and what is their average behavior?
3) Is there a relationship between smooth driving and safe behavior?

The remainder of the paper is organized as follows: first, the main findings of previous relative works are discussed and, then, the methodological tools that are used, as well as the data collected, are described. Subsequently, the results of the analysis are presented and finally, conclusions and suggestions for future research are drawn.

METHODOLOGY

Overview

Driving behavior refers to the way in which a driver executes the driving task and is also known as "driving style". In this paper, driving behavior is analyzed by following a two-step methodology that is applied on two levels, a trip and a driver level. On a trip level, trips are separated into clusters with similar characteristics, using the K-means algorithm, which correspond to different driving profiles based on the level of smoothness of the driving task. The most suitable number of clusters k was defined using the elbow method, while the evaluation of the clustering results was performed by estimating the silhouette index. The driving parameters used for the partition of the trips into groups with similar characteristics include statistical measurements of acceleration and deceleration, acceleration after a stop and the smoothness indicator.

The safety efficiency is estimated on a driver level in the second step based on DEA. The output of this step is the assignment of an efficiency index to each driver based on the critical safety-related metrics mentioned above, the total number of HA and HB events, total duration of mobile phone usage and total duration of driving over the speed limits. The efficiency index will represent the overall safety behavior of each driver for the recorded period. Finally, a synthesis of the results takes place to understand the relationship between smooth and safe driving, including the estimation of two correlation significance coefficients, namely Kendall's tau and Spearman's rank correlation coefficients. More details on the specific methodologies applied in this study are provided below.

K-Means Clustering

K-Means is one of the best-known clustering methodologies that aims to group the data into a number of clusters k previously specified by the researcher (*27*). One of the most commonly used metrics for comparing results across different values of k is the mean distance between cluster centroids and the data points assigned to each one of them. When this metric is plotted as a function of the number of clusters, k can be used to estimate the "elbow point", which is the point where the rate of this metric's decrease sharply shifts. Several driver profiling studies have used the K-Means algorithm to identify the existing profiles (*8*, *21*, *28*). This algorithm can cluster several subjects into groups with similar behavior based on multiple features.

While using the K-means clustering method, the goal is to partition the dataset into a predefined number K of clusters. A cluster can be thought of as comprising a group of data points whose inter-point distances are small compared with the distances of points outside of the cluster. For each data point X_n, a corresponding set of binary indicator variables $r_{nk} \in \{0,1\}$ are introduced, where $k = 1, \dots, K$ describing which of K clusters the data point X_n is assigned to, so that if a data point is assigned to cluster k then $r_{nk} = 1$, and $r_{nj} = 0$ for $j \neq k$. Then, an objective function is defined, given by:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} \| x_n - \mu_k \|^2 \tag{1}$$

which represents the sum of squares of the distances of each data point to its assigned vector μ_k, where μ_k represents the center of the k^{th} cluster (*29*). In order to evaluate the goodness of clustering results the Silhouette index is estimated ranging between [-1,1] and is interpreted as follows: 1 means that the clusters are very dense and nicely separated while 0 means that clusters are overlapping.

Data Envelopment Analysis

DEA is a mathematical programming technique with minimal assumptions that determines the efficiency of a Decision-Making Unit (DMU) based on its inputs and outputs and relatively estimates efficiency to the rest of the units involved in the analysis. A Decision-Making Unit (DMU) is "technically efficient" when the number of outputs produced is maximized for a given number of inputs, or for a given output the number of inputs used is minimized (*30*). Thus, when a DMU is technically efficient, it operates on its production frontier and therefore DMUs lie on the efficiency frontier (*31*). DEA is a non-parametric approach that does not require any assumptions about the functional form of a production function and a priori information on the importance of inputs and outputs.

The concept of DEA is to minimize inputs (input-oriented model) or maximize the outputs of a problem (output-oriented model) (*31*). More specifically in the present study, a driver should either drive more kilometers maintaining the same number of harsh braking/ accelerating events or reduce the number of harsh braking/accelerating events for the same mileage. The same applies, of course, to the rest of the metrics recorded for each driver. From a road safety perspective, increasing mileage increases the exposure of a driver and consequently crash risk (*18*) and, therefore, an input-oriented (IO) DEA model is developed aiming to minimize inputs (recorded metrics) while maintaining the same number of outputs (recorded distance).

Previous research also showed that the driving efficiency problem is considered a constant-returns-to-scale (CRS) problem and that the sum of all metrics (inputs) recorded such as the total number of harsh acceleration and braking events that occurred by each driver changes proportionally to the sum of driving distance (output) (*3*). This is deemed to be a correct assumption on a trip basis since (a) all variables used are continuous quantitative variables as those used in previous DEA studies (*23*, *24*) and (b) a driver should reduce his mileage (*18*) and the frequency of some of his driving characteristics such as harsh acceleration and braking, mobile phone usage and speeding (*18*, *32*). It is also implicitly assumed that the driving efficiency problem is a CRS problem and that the average and sum of all metrics (inputs) recorded, such as the number of harsh acceleration and braking events, changes proportionally to the sum of driving distance (output).

For the sake of simplicity, it is noted that from now on DMUs will be referred as drivers. In order to evaluate the driving efficiency of Driver$_0$ and assuming a sample of N drivers, let X and Y represent the set of inputs and outputs respectively, for the rest of the drivers' sample. In other words, $X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_i\}$ and $Y = \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_i\}$ where $i \in [1, N-1]$. Considering each driver as a DMU and taking into account the principles of DEA (*33*), the mathematical formulation for the specific driving efficiency problem examined herein is $min(Driving\_Efficiency_0)$. Subject to the following constraints:

$$\begin{gathered} Driving\_Efficiency_0 * x_0 - X * \lambda \geq 0 \\ Y * \lambda \geq y_0 \\ \lambda\_i \geq 0 \forall \lambda\_i \in \lambda \end{gathered} \tag{2}$$

where λ_i is the weight coefficient for each $Driver_i$ that is an element of set λ, X is the set of Inputs, Y is the set of outputs and $Driving\_Efficiency_0$ is a scalar representing the efficiency of reference driver i.e., $Driver_0$. Apparently, the use of the sets in the constraints indicates the creation of (N-1) inequalities when "building" the constraints of the linear problem i.e., $1 + 3 * (N - 1) = 3 * N - 2$ constraints. The rationality behind these constraints is to ensure that, compared to the rest of the sample, there could not be any other X, Y combination leading to a higher efficiency than that of the driver being evaluated. The set of λ estimated from the linear program is positive only for those drivers who act as peers to the driver being evaluated and is used afterwards to estimate the efficient level of inputs for the inefficient drivers (*driving efficiency <1*) that each driver should reach to become efficient. The objective function of DEA is min $Driving\_Efficiency_i$ i.e., to determine the minimum efficiency of $Driver_i$ that satisfies the above conditions.

Rankings correlation metrics

In order to investigate the correlation between two rankings and conclude about its significance, dedicated statistical tests should be conducted. In contrast to the comparison between population samples, where the mean values of specific attributes of the sample are taken into account, the comparison between rankings is performed by evaluating the divergence in the ordering of each individual (e.g. driver) in each ranking. The most well-known metric to measure the ordinal association between two rankings is Kendall's tau coefficient. Let x_1, x_2 and y_1, y_2 be the scores of two individuals in two different rankings; this pair of observations is called concordant if either $x_1<x_2$ and $y_1<y_2$ or $x_1>x_2$ and $y_1>y_2$, otherwise it is called discordant. Kendall's tau is calculated as follows (*34*):

$$tau = \frac{(number\ of\ concordant\ pairs) - (number\ of\ discordant\ pairs)}{(total\ number\ of\ pairs)} \tag{3}$$

The coefficient ranges between -1 and 1, indicating perfect disagreement and agreement, respectively, between the two rankings. A variation of Kendall's tau is the concordance index, which is simply estimated as the percentage of concordant pairs.

Although Kendall's tau is an efficient and intuitive metric, it has the drawback that it only evaluates the concordance between each pair of observations and not the magnitude of its diversity between each pair, so that big and small dissimilarities between the rankings are all equally taken into account. For this reason, Spearman's Rank Correlation is also exploited in this work. It is a variation of the classic Spearman's coefficient, which takes into account the difference in the ordering of each observation in two rankings, instead of in the actual score value. For example, this difference would be 1 if an individual is ranked 1st based on one criterion and 2nd based on the other. More formally, Spearman's rank coefficient is given by the following equation (*35*):

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{4}$$

where d_i is the difference between the two ranks of observation i and n is the total number of observations. Spearman's rank coefficient also ranges between -1 and 1. A value of -1 indicates a perfect negative correlation (all observations are ranked differently), while a value of 1, in contrast, indicates perfect matching of the rankings.

DATA COLLECTION

Driving data is collected from an already developed smartphone application which is always running in the background of the smartphone's operating system in a way that no user action is required while driving. Using several criteria, the application starts to collect raw data from smartphone sensors such as accelerometer, gyroscope and GPS. Since the application is using cloud-based services, after the automatic detection of the end of the trip, data is uploaded to the server for storage in an anonymized way for further processing. For each trip, numerous variables that describe driving behavior are available including, but not limited to, statistical measurements of acceleration, deceleration and speed. In addition, speeding measurements are collected that describe speed excess driving, as well as mobile usage indicators, are estimated that describe how cautious the driver is. The driving parameters used for the specific research are given in **Table 1**, together with the methodological step in which they were used.

TABLE 1 Description of driving parameters used in each methodological step

Variable	**Description**	**Clustering [trip profiles]**	**DEA [overall driver efficiency]**
Harsh acceleration events *(HA)*	The number of harsh acceleration events during the trip	✓	✓
Harsh brakes events *(HB)*	The number of harsh brake events during the trip		✓
Average acceleration *(acc_avg)*/ deceleration *(dec_avg)*	The average acceleration / deceleration of the trip	✓	
Max acceleration *(acc_q90)*/ Min deceleration *(dec_q90)*	The 90% quartile of the trip's acceleration / deceleration	✓	
Acceleration from stop *(acc_from_stop)*	Average acceleration after stops	✓	
Smoothness indicator *(smooth_eco)*	The sum of differences of squares of final and initial speed, divided by trip distance.	✓	
Percent of mobile usage	The percentage of trip duration when the driver uses his/her mobile phone.		✓
Percent of speeding	The percentage of trip duration when the driver drives over the speed limit.		✓
Driving distance	The total distance traveled during the trip.		✓

Trips were excluded from the analysis performed in this study based on the criteria of duration, distance and road type. To this end, trips with a duration lower than 10 minutes and a distance lower than 5 kilometers were excluded as well as trips that took place on a highway. Since driving behavior changes from trip to trip even for the same driver, in order to capture the main (average) driving profile of each individual a minimum of 100 trips per driver was set as the lower limit for a driver to be included in the analysis. Having applied the above filters, the dataset used for the present paper includes more than 220,000 trips made by about 760 unique drivers all around Greece. All data was provided by OSeven Telematics in a fully anonymized format.

RESULTS

Profiling at a trip level and driver performance evaluation

The first step of the methodology includes the characterization of the driving profile at a trip level also referred to as "trip profile". For the definition of the most appropriate number of clusters the well-known elbow method was used as shown in **Figure 1**. Based on this, the trips should be separated into 3 distinct clusters.

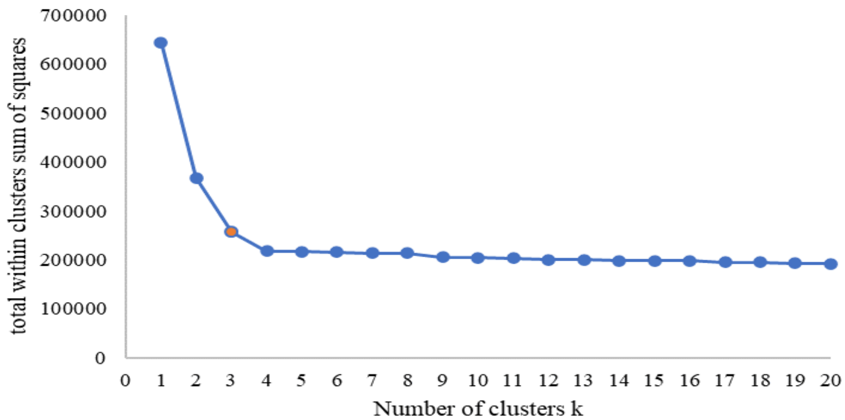

Figure 1 Selection of the number of clusters using the elbow method

Using the K-means clustering algorithm, the trips are separated into 3 distinct trip profiles each one of them indicating a different driving style: smooth behavior, rough driving and intermediate behavior. **Table 2** presents the centers of each cluster for each driving parameter. Results indicate that around 23% of the trips are featured by rough driving characteristics, while a corresponding proportion of trips are characterized by smooth driving behavior. The silhouette index of the clustering was estimated 0.51.

TABLE 2 Clustering centers and number of trips per trip profile

	acc_avg	acc_q90	dec_avg	dec_q90	smooth_eco	acc_from_stop	Number of trips [%]
rough driving	1.671	3.728	-1.839	-0.246	0.402	5.502	53,205 [23.2%]
intermediate behavior	1.275	2.827	-1.442	-0.198	0.305	3.922	126,749 [55.3%]
smooth driving	0.950	2.083	-1.091	-0.155	0.230	2.239	49,349 [21.5%]

Based on the findings, smooth driving is related to significantly lower measurements of acceleration and deceleration compared to the rest of the trip profiles. In addition, as it turned out, there is a critical threshold under which the acceleration from stop indicates a smooth driving behavior at 2.239 m/s^2. This finding is also in line with previous research, which has shown that the acceleration after a stop should not exceed 2.598 m/s^2 (*36*). Moreover, the smoothness indicator that corresponds to the differences in speeds during the trip, has its lowest value in the case of the smooth profile revealing that smooth driving is associated with a few changes in speed. **Figure 2** illustrates the relationship between these two driving parameters.

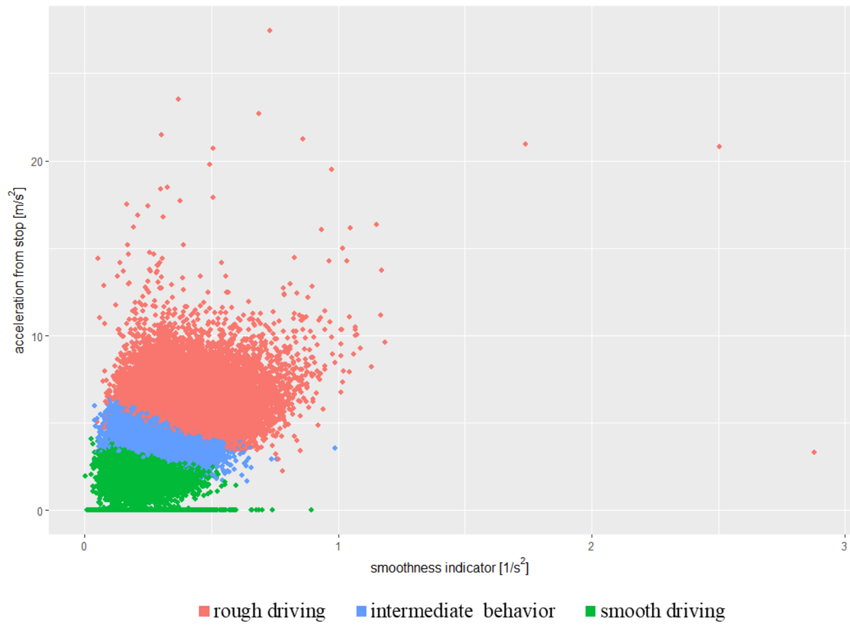

Figure 2 Relation between smoothness indicator and acceleration from stop per trip profile

The clustering analysis has revealed three driving profiles characterized by different levels of smoothness of the driving task. In order to gain some more insights on how smooth driving differentiates from the rough driving style, the boxplots of average and maximum acceleration and average deceleration are presented below (**Figure 3**). Based on the results, smooth driving is characterized by significantly low values of acceleration and deceleration and, at the same time, the range of values is significantly smaller compared to that in the rough driving profile. It can be concluded that drivers adopting a smooth driving behavior share more common driving characteristics while trips of the aggressive profile are more differentiated in terms of acceleration and deceleration choices.

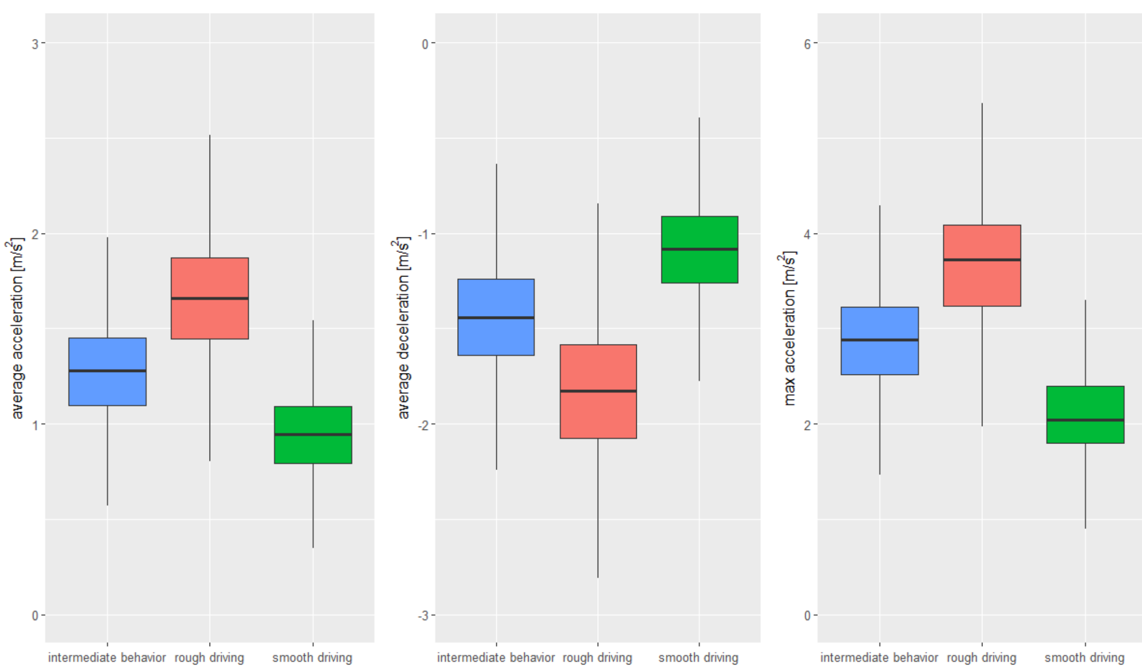

Figure 3 Boxplots of acceleration measurements for the three trip profiles

For the purposes of this research, a smooth driving score was used in order to rank the drivers based on the distribution of their trips among the three profiles. As the three profiles are connected with increasing smooth driving behavior, the score for the i[th] driver is calculated using the following simple formula:

$$Smoothness\ score\ (i) = P_{smooth} * 3 + \ P_{intermediate} * 2 + P_{rough} * 1 \tag{5}$$

where P_{smooth}, $P_{intermediate}$ and P_{rough} are the percentages of the trips of driver i that belong to smooth, intermediate and rough profile, respectively. Smooth trips are rewarded with 3 points, intermediate with two and rough ones with 1, so that a higher score indicates a smoother driver. The drivers are then ranked based on the above score.

Driving safety benchmarking

Based on the results of the DEA analysis, a safety efficiency index is assigned to each driver. Drivers are divided into 4 groups based on their efficiency using the 4 quartiles ranging from 0% to 100%, with 100% being the highest possible efficiency. The average metric values for the 4 DEA inputs considered in the model, i.e., the number of HA and HB, and the duration of smartphone usage and speeding, per 100km are displayed in **Table 3**. It is observed that average metric values are lower for driver groups with higher efficiency, with the highest similarity being observed between drivers that belong to the 50-75% and 75-100% quartiles. For instance, the least efficient drivers use their mobile phones 2.8 times more and they drive over the speed limit 2.2 times more than the most efficient ones. Regarding harsh events, the least efficient drivers perform 3.9 times more HA and HB events than the most efficient drivers.

TABLE 3 Average metric values for each different quartile

Safety efficiency quartile ranges	Average number of HA per 100km	Average number of HB events per 100km	Average minutes of mobile usage per 100km	Average minutes of speeding per 100km
0% - 25%	11.2	18.6	6.4	12.8
25% - 50%	7.2	11.3	5.9	10.3
50% - 75%	4.8	7.6	4.0	7.1
75% - 100%	2.9	4.8	2.3	5.7

Since it is not feasible to illustrate the DEA model described above since it has 4 dimensions (4 DEA inputs by 1 DEA output), a model with lower dimensions is shown in **Figure 4** in order to describe the functionality and graphically represent the DEA results. It should be highlighted at this point that models incorporating two-inputs/one output or one-input/two outputs can only be visualized in 2-D figures. **Figure 4** illustrates the indicative efficiency frontiers for a safety efficiency DEA model that takes into account only the number of harsh acceleration and braking events as DEA inputs and the total driving distance as DEA output.

The logarithm of distance/HA and the logarithm of distance/HB are plotted on axis X and Y respectively, together with the envelopment line that accounts for the efficiency frontier. Extending the line joining the origin and each DMU_i, it crosses the efficiency frontier at a point where virtual DMU_i is created which represents the optimal performance that the specific DMU_i can achieve. The closer a driver is to the efficiency frontier, the higher their efficiency index is. As it appears, there are only two efficient drivers in this illustrative example compared to which, the efficiency index is calculated for the rest of the drivers.

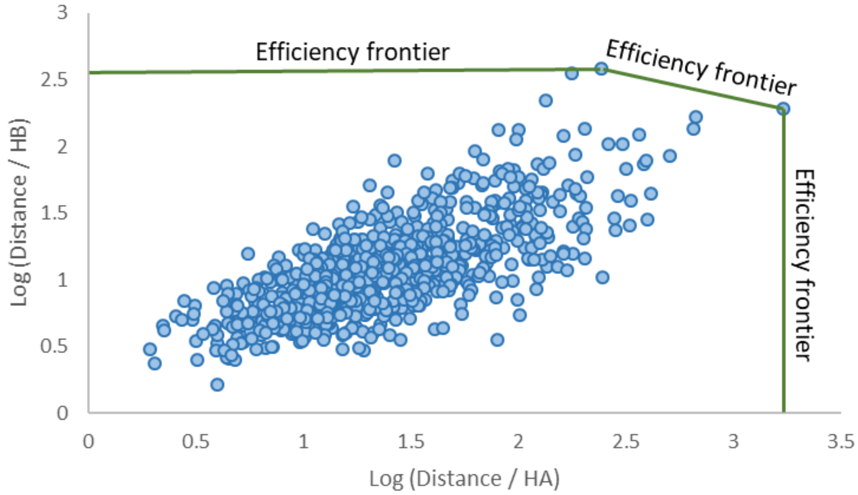

Figure 4 Indicative efficiency frontiers for drivers' safety based on harsh acceleration and braking events

DISCUSSION

Driving trip profiling revealed 3 distinct trip profiles representing smooth behavior, rough driving and intermediate behavior. The smooth driving trip profile was found to be related to significantly lower measurements of acceleration and deceleration compared to the rest. Trips that belong to the aggressive profile are more different in terms of acceleration and deceleration whereas smoother trips share more common driving characteristics. Safety efficiency evaluation indicated that the four efficiency groups of drivers illustrate similarities and dissimilarities depending on the driving metric considered. For instance, the average minutes of mobile usage and overspeeding do not significantly differ for drivers of the two lowest efficiency quartile ranges, whereas the difference in the number of HA and HB events is higher. The highest value range between the most and least efficient drivers is observed in the average number of harsh events per 100 km.

A synthesis of the results of trip smooth driving clustering and driver safety benchmarking will provide insights into the relationship between smooth driving and safe behavior. The results of this synthesis are presented in **Figure 5**. Drivers in this table are split into the 4 quartiles of overall driver safety efficiency. It appears that the distribution of trips of the drivers that belong to each safety efficiency percentile range across the three different trip clusters displayed in **Table 2**. For instance, 38% of the trips performed by the drivers that belong to the first quartile range were trips characterized by rough driving, whereas 8% and 54% of total trips refer to smooth and intermediate driving behavior, respectively. It is evident that the percentage of aggressive trips is significantly lower in the second quartile of driver safety efficiency compared to the first. Nonetheless, this reduction rate is slightly reduced when moving to higher efficiency quartiles of drivers. The percentage of smooth trips is steadily increasing when moving to quartiles of more efficient drivers showing a strong correlation between smooth driving and the safety efficiency index. On the other hand, the percentage of moderate trips appears to be weakly correlated with driver's safety efficiency. All the above are an indication of an existing relationship between smooth driving and safe behavior.

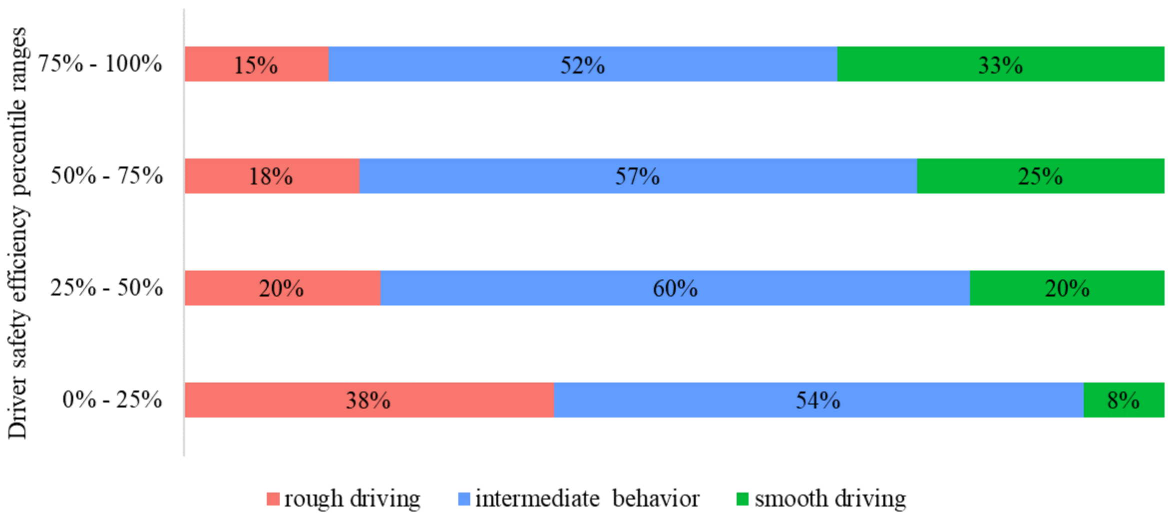

Figure 5 Distribution of trips across smooth driving trip clusters for each quartile of driver safety efficiency

Finally, in order to more thoroughly investigate the correlation between the two behavior rankings, two relevant statistical tests are performed and the corresponding coefficients are calculated; Kendall's (concordance) tau index and Spearman's rank order correlation. As already mentioned earlier, Kendall's tau takes into account whether the relevant ranking of a pair of drivers is the same based on both criteria or not, i.e. whether the safer driver is the smoother as well, and not the amount of a possible divergence. On the other hand, Spearman's rank order correlation is calculated based on the divergence in the ranking of the driver in the two ranking lists (e.g. for a driver that is 10th on the first and 12th on the second, the anticipated divergence is 2) and not the actual values of the two scoring systems. This is suitable for the present work, as the two scoring systems have different value scales that cannot be directly compared.

The value of Kendall's tau that was estimated for the two rankings, safety and smooth driving, is 0.42 and the corresponding concordance index is 0.71, which indicate a strong and statistically significant correlation between them. These numbers can be interpreted as that 71% of the driver pairs are ranked in the same manner based on both criteria, i.e. a safer driver is also a smoother one 71% of the times. Moreover, Spearman's rank order correlation coefficient is estimated at 0.69, with a p-value<0.0001, which also indicates a significant and positive correlation, i.e. a safer driver drives is also smoother and vice versa.

CONCLUSIONS

Eco-driving and driving safety are the two main priorities for the urban road network, especially when individual driving behavior is considered. In this paper, we took advantage of a large naturalistic driving dataset in order to investigate the relation between smooth driving and safe driving as they emerged in two distinct levels of driving behavior, namely at a trip level where trip profiles are defined and a driver level. At a trip level, driving behavior is categorized based on different levels of smoothness during driving. Specifically, three trip profiles were identified using a k-means clustering algorithm: smooth, rough and intermediate driving and the drivers were ranked based on the distribution of their trips among the three profiles. Then, using the DEA, driving efficiency in terms of safety was investigated at a driver level.

Findings indicated that there exist significant differences between the safety-related driving parameters among the four quartiles of driving efficiency. It was found that the percentage of trips with intermediate level of smoothness does not significantly differ between drivers of higher and lower efficiency. On the contrary, the percentage of rough and smooth trips that most efficient drivers perform is remarkably lower and higher, respectively, than the respective percentage of the least efficient drivers. This study also revealed a strong relationship between smooth driving and safe driving behavior, which is statistically significant, as indicated by the results of the two statistical tests that were performed. Finally, the higher percentage range observed in smooth trips is an indication that smooth driving is a more important factor for forecasting safe driving than aggressive driving.

The importance of understanding the relationship between smooth and safe driving is high, as it shows the potential of predicting safe driving behavior through smooth driving parameters, when information on safety parameters is not available, and vice versa. Potential applications of this research include the evaluation of smooth and safety behavior as well as the development of a recommendation system that provides feedback to drivers in order to improve driving behavior in terms of smoothness and safety. As a future step, the predictability of smooth behavior based on safety attributes, and vice versa, should also be examined. It is also recommended that this analysis will be extended in the future, considering also the different road types. Finally, it would be valuable to also take into account data that were not available in this study such as fuel consumption at a trip level and crash records on a driver level.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: E. Mantouka, P. Fafoutellis, D. Tselentis, E. Papadimitriou, E. Vlahogianni; data analysis: E. Mantouka, P. Fafoutellis; interpretation of results: E. Mantouka, P. Fafoutellis, D. Tselentis; draft manuscript preparation: E. Mantouka, P. Fafoutellis, D. Tselentis, E. Papadimitriou, E. Vlahogianni, G. Yannis. All authors reviewed the results and approved the final version of the manuscript.

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